Convergence in Science: Growth and Structure of Worldwide Scientific Output, 1993-2008

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***Abstract*— We examine if the globalisation of science is accompanied by convergence in the level and structure of scientific output. We use Web of Science data on the scientific output of 205 countries for 1993, 2000, and 2008, distinguished by subject area. We found evidence of absolute and conditional β-convergence and σ-convergence in levels of scientific output, particularly after 2000. The data also show that the portfolios of the majority of the world's science systems are becoming more similar. This convergence of portfolios occurs in convergence clubs rather than as a global process. Exploratory factor analysis shows that countries cluster into eight discrete convergence clubs and perhaps only two: the 'haves' and 'have-nots'. Dynamic shift-share analysis reveals that growth is a normal phenomenon, output composition is only really an issue in the former Soviet Republics (negative) and the LDCs (positive) after 2000, and comparative advantages is where convergence clubs differentiate strongest. The ability of countries to improve local conditions and escape the strictures of their portfolio depends on the interplay of forces along two dimensions. between short-term dynamics and long-term stability and between the complexity of science and the predominance of national policies and institutions. Understanding the design and functioning of a science system in all its complexity is crucial to survive in a world of different speeds with intense competition and persistent gaps between rich and poor. For scientists and policy makers alike, selecting the right science portfolio and knowing the competition are key issues.**

***Index Terms*— convergence; science; globalisation; specialization; comparative advantage**

I. Introduction

MANY view science as an outstanding example of globalisation. The dynamics of scientific research are global in nature, especially in such fields as high-energy physics and climatology. Science has become a global community in which researchers produce for a worldwide commons, or, as Leclerc and Gagne [1] would have it, "a vast single market for the exchange of research products". An important aspect of the globalisation in science is, what Giddens [2] calls, "the intensification of worldwide social relations". Scientists increasingly collaborate internationally [3, 4], especially in big science but also, increasingly, in other fields (Georghiou 1998). They build social networks that are bound by the limits of their specialisation rather than by national borders [cf. 5].

Globalisation does not appear to have brought the science systems of the world much closer together. There remain vast differences in S&T performance among the world's nations. Efforts to understand these differences generally focus on the relation between aggregate outputs and inputs or preconditions [see, e.g., 6, 7], even though it is understood that aggregate numbers hide significant details [8]. Yet, there is good reason not to expect globalisation to produce convergence. Science and technology represent a competitive advantage and in an open world it is of vital importance for national governments to protect national interests [9].

In this paper, we examine if the globalisation of science is accompanied by convergence in the level and structure of scientific output. In section 2 we develop the theoretical reasons for convergence. Using scientific output data for 205 countries in 1993, 2000, and 2008 (explained in section 3), we examine if levels of scientific output are growing closer together (section 4). Are small countries growing faster than large countries? In section 5, we study the degree of similarity among the world's science systems. Are national science portfolios converging towards a global agenda? Or does convergence occur within convergence clubs? In section 6, we examine the interplay between growth and structure using dynamic shift-share analysis. We draw conclusions and discuss their implications in section 7.

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II. AGENDA SETTING, RESOURCE ALLOCATION AND CONVERGENCE IN SCIENCE

Society invests in knowledge for various reasons; knowledge is inherently valuable, science is expected to produce major long-term benefits, and innovation provides nations with a competitive advantage. The allocation of resources for science calls for a dual assessment of opportunity costs.[1] In the allocation of scarce (public) resources – the expression of the social contract between science and society [10, 11] – the relevant choice is one between investing in science, with its uncertain, intangible returns and long time frame, and investing in more immediate and tangible opportunities, such as health care, education, or transport infrastructure. Aggregate levels of output tell us something about the returns to society's investment in science. Within science, resources are allocated to institutions and specialisations through a variety of channels, such as block grants to universities, organisational allocation mechanisms, competitive funding programmes, investments in large-scale research facilities and transdisciplinary research programmes, etcetera [12]. At this level, opportunity costs refer to the scientific and social promises of specialisations, and the choice between investing in infrastructures for future research and expenditure on current research. The result is reflected in the composition of the national scientific research agenda.

Agenda setting in science can be understood as a form of portfolio management. However, the term management presumes a much higher degree of conscious, rational decision making than actually occurs. Agenda setting involves a multitude of actors at various levels in the science system, from the individual researcher in his or her discrete niche, to universities and institutes with a multifaceted mission, and research councils, science foundations, and government ministries that make policy and set priorities. We can model scientific specialisation patterns as the outcome of a social contract between science and society, but there may be many social contracts between many different principals and agents [13]. This implies that national or global research agendas are emergent, arising from the interaction between a multitude of heterogeneous actors, with a wide range of specialisations and private research agendas, located in all sectors and at all levels of the science system. Agenda setting is a complex adaptive process. When we look at national patterns of specialisation, we see the emergent outcome of that process.

In a complex system, outcomes depend on the rules that drive the behaviour of individual agents and the interactions between those agents. Individual researchers look for opportunities to achieve priority and build a reputation [14-16], which requires a careful selection of specialisation. Priority determination and reputation building necessitate interaction. Researchers respond to agenda setting in their cognitive and institutional environment, moving into or out of niches depending on opportunities provided by, for example, priority setting in national funding programmes or the global rise of highly dynamic fields such as nanotechnology.

Interaction intricately links agenda setting to resource allocation. Scientific fields have different search regimes, defined in part as a set of interdependent resource requirements [17]. Any decision on the part of an individual scientist, a research group, a department, faculty, organisation or government to focus on a particular scientific specialisation, calls for a strategy to mobilise those resources. Since resources are by definition scarce, mobilising resources inevitably involves competition. Researchers collaborate to gain access to expertise, research facilities and databases [18]; groups, institutions and firms try to attract star scientists [19]; actors from science and industry build social networks and consortia to grasp a share of large investment programmes (e.g. the EU Framework Programme); and so on.

In theory, the range of possible specialisation outcomes is infinite. We might assume that autonomous researchers make independent decisions, driven by their curiosity and creativity, and that the institutional and financial dynamics of agenda setting are entirely national. The result would be a unique specialisation pattern for every country. However, in most disciplines scientific discourse is global and international scientific collaboration is on the rise. Collaboration reflects similarities in specialisation as well as geographic and cultural proximity [20, 21]. Individual researchers may have local autonomy in setting their agenda. But if they are to gather reputation, their autonomy is bounded: they must latch onto existing, worldwide research agendas. Given that science and innovation are highly competitive policy arenas, there will be global dynamics underlying national decision making. National and regional governments, universities, and industries shape their research agendas in constant interaction with counterparts in other countries. And even though evidence on the link between scientific excellence and economic competitiveness is tenuous, scientific specialisation is directly relevant to attaining a strong position in science-based industries [22].

This means that national research agendas are constructed both autonomously – by individual actors within a national system, guided in part and to varying extents by national policy – and interdependently –through interaction between researchers, institutions, and science systems. Consequently, we expect that there will be a large degree of similarity in national specialisation patterns. Similar nations make similar autonomous choices.

[1] An assessment of opportunity costs in decision making involves marginal rather than absolute costs, focusing on the allocation of additional resources or a shift of resources from one opportunity to another (e.g. from education to science; from fundamental science to applied science).

There may even be a single, common worldwide structure to scientific output, a structure that drives the convergence of national scientific portfolios.

The salient features of globalisation, most notably the steady increase in international scientific collaboration, work in favour of an increasing similarity in scientific portfolios. Collaboration aligns research agendas. Large funding programmes, such as the EU Framework Programmes and collaborative infrastructures like CERN and ARGO, provide smaller countries the opportunity to enter more resource-intensive research areas. Particularly where it concerns smaller and poorer nations, we can expect a degree of similarity in scientific output based on national needs and comparative advantages. Since the scarcities and urgent needs of small countries will most likely be comparable, we may expect to find clusters of small science systems with similar research portfolios. In short, we expect to find convergence in national science portfolios.

Our conceptual framework culminates in two broad questions on convergence. (1) Is there convergence in levels of scientific output? The simple approach to this question is to ask whether small science systems grow faster than large systems and if international differences in output per capita have decreased. (2) Is there convergence in the structure of scientific output? If there is convergence in output levels, we should also expect growing science systems to exhibit declining degrees of specialisation. It follows that as output is more evenly distributed across research areas, the probability of similarity between output structures increases. Provided output growth is evenly distributed across countries or at least biased towards smaller science systems, we can expect scientific output structures to converge over time. However, it is not unlikely that growth is not evenly distributed and that the scientific portfolio of some countries converges faster than others. Castellacci and Archibugi [23] found three technology clubs with considerable differences in innovative capability and levels of technological infrastructure and human skills. Similar clubs may exist in science. Does worldwide scientific output converge towards a global macrostructure or are there discrete convergence clubs? What distinguishes those clubs?

III. Data and methods

Our analysis is based on publication data extracted from the five citation databases of the Web of Science (Science Citation Index Expanded, Social Sciences Citation Index, Arts & Humanities Citation Index, Conference Proceedings Citation Index-Science, and Conference Proceedings Citation Index-Social Science & Humanities). For every country, the total set of publications was extracted using a topic search of the form "cu=[standardised country name] and py=[year]".[2] Each country's output was classified into the 246 subject areas of the Web of Science, using its online analysis tool. In doing so, we collected a dataset for the entire world in 1993, 2000 and 2008.[3]

Our search method does not cover total output to the last publication and by using a single source we subject our analysis to the biases inherent to that source. On the other hand, Meho and Sugimoto [24] compared the Web of Science with Scopus and found that on the level of entire countries and research domains, the results are very similar. For the purpose of our analysis it is not necessary for the dataset to cover all output, just that it be balanced and representative. The representativeness of the data is given by the scale and scope of the Web of Science. Balance does require an adjustment: we exclude the social science and humanities. A tentative test of the international distribution of output suggests an Anglo-Saxon bias in such areas as literature and arts. More significant, however, is that the intensive efforts of Thomson Reuters to expand the Web of Science's coverage of the social sciences and humanities create the possibility of a statistical artefact in the results: we might be measuring database expansion rather than real changes in science over time. The dataset consequently covers 169 subject areas.

Our search method produces two kinds of double counting. We double count the output of different nations by assigning a full count to papers produced in international collaboration. World output is consequently overestimated. The result does provide a good indication of the number of instances a researcher from a country was involved in the production of scientific output. As such, output as we define it is as a proxy for resource allocation to and within science.

We also double count the output in different subject areas. This will tend to inflate output in highly multidisciplinary research areas at the expense (in relative terms) of monodisciplinary areas. Unless there is a strong national or regional bias towards highly multidisciplinary research, we may assume that subject area inflation has an equal effect on all countries and that national output by subject area provides a good account of national resource allocation.

[2] We had to take into account changes in political boundaries (e.g. in Yugoslavia), adjust for spelling errors, and look for creative approaches for countries with more than 100,000 publications per year, the Web of Science's online search limit. For the USA, we extracted publications by searching on addresses containing the formal state code, e.g. ad=", CA " for California.

[3] We tested the annual number of hits for countries sensitive to changes around 1990, such as in Germany, Yugoslavia en the former Soviet Union. By 1993, political turmoil appeared to have ended and the Web of Science had adjusted to the new political boundaries.

We have borrowed methods from two broad methodological traditions. First, there is a rich literature on specialisation in technology and international trade. Various authors have developed specialisation indices and comparative measures for the similarity of compositional data. The second methodological stream concerns comparative studies of (economic) growth and structure. Methods are explained in more detail where they are used.

IV. Growth

A. *β-convergence and σ-convergence*

Convergence in terms of growth implies that smaller science systems grow faster than larger systems and that the dispersion in levels of scientific output per capita declines. Macroeconomic analysis provides instruments for the study of convergence. Barro and Sala-i-Martin [25, 26] distinguish between two types of convergence: β-convergence occurs when poor economies tend to grow faster than rich economies, while σ-convergence indicates that the dispersion of levels of real per capita GDP tends to decrease over time.

We measure growth in terms of per capita scientific output. Using the method of Barro and Sala-i-Martin gives

$$\phi_{t,t+T} = \alpha + \beta \log(y_t) + \varepsilon_t, \qquad (1)$$

where $\varphi_{t,t+T}$ is the annual growth rate of national per capita scientific output (defined as the difference between $log(y_{t+T})$ and $log(y_t)$, divided by T) and $log(y_t)$ is per capita scientific output at time t. If β is lower than zero, there is β-convergence. Higher initial levels of per capita scientific output negatively affect rates of growth.

σ-convergence can be interpreted as a decrease in differences in per capita scientific output, and occurs if:

$$\sigma_{t+T} < \sigma_t \qquad (2)$$

where σ_t and σ_{t+T} are the standard deviations of $log(y_t)$ at times t and $t+T$.

The results are shown in Tables 1 and 2. There appears to have been neither convergence nor divergence in 1993-2000. The results do clearly show β-convergence in 2000-2008: smaller science systems grow faster than larger science systems. The test for σ-convergence shows stability in 1993-2000. After 2000, the dispersion of output levels declined. The results for σ-convergence concur with those for β-convergence.

TABLE 1.

B-CONVERGENCE IN WORLDWIDE SCIENCE, 1993-2008

	1993-2000	2000-2008	1993-2008
β, per capita output (log)	.006	-.008***	-.002
	(.104)	(.000)	(.339)
N	181	191	182

Sources: Population from the United Nations Common Database (UNCDB). Scientific output from the Web of Science. p-values between brackets.

TABLE 2.

Σ-CONVERGENCE IN WORLDWIDE SCIENCE, 1993-2008

	1993	2000	2008
coefficient of variation, per capita output (log)	.614	.614	.524
N	183	193	195

Note: Estimates concern coefficients of variation, i.e. standard deviation normalised for mean of per capita output.
Sources: Population from the United Nations Common Database (UNCDB). Scientific output from the Web of Science.

Thus far we have looked for *absolute* convergence, which occurs when there is an inverse relation between growth rates of scientific output and initial output levels. It is fairly obvious that output growth is the result of a more complex process involving a wider set of determinants. We should also look for *conditional* convergence. Is there still a significant inverse relation between scientific output growth and initial output levels when controlling for intermediary variables?

It is not our aim to provide a complete explanation for the growth of scientific output. We merely want to know whether, after controlling for a reasonable set of potential determinants and using the best available data, we still find convergence. Our tests boil down to three models: (1) a resource-based view on national scientific performance, using per capita GDP and population; (2) a knowledge production function based on GERD and the number of researchers; and (3) S&T capacity using per capita GDP, the number of researchers, and gross tertiary enrolment.[4] Different combinations of determinants have been tested to establish their marginal impact on the coefficient of the initial output level.

For 1993-2000, our models confirm the absence of conditional β-convergence (Table 3). The coefficients for the initial level of output are not significant. For 2000-2008, all models indicate that there is conditional β-convergence. After controlling for additional explanatory variables, the coefficient for initial output levels remains strong and negative.[5] This confirms our initial findings.

TABLE 3.

TEST RESULTS FOR CONDITIONAL Β-CONVERGENCE

	1993-2000		2000-2008		
	resource-based	knowledge production function	resource-based	knowledge production function	S&T capacity
constant	.043*	.093***	.116***	.156***	.220***
	(1.967)	(4.267)	(7.278)	(8.532)	(6.837)
initial level of per capita scientific output	-.000	-.004	-.010***	-.017***	-.024***
	(-.020)	(-.949)	(-4.045)	(-4.444)	(-5.657)
real per capita GDP growth	.868***		.144		-.499**
	(3.816)		(.782)		(-2.074)
population growth	-1.677**		-10.815		
	(-2.453)		(-1.596)		
growth of GERD ratio		-.163		.077	
		(-1.152)		(.498)	
growth of researchers per million inhabitants		.316**		.260	.478***
		(2.345)		(1.397)	(2.992)
growth of gross tertiary enrolment ratio					-.012
					(-.149)
R^2	.127	.138	.092	.273	.465
F	8.579	2.035	6.310	6.775	8.486
	(.000)	(.125)	(.000)	(.000)	(.000)
N	181	42	191	58	44

Note: Dependent variable is the growth of per capita scientific output. Results refer to unstandardised coefficients of linear regression models. The S&T capacity model could not be estimated for 1993-2000 for lack of enrolment data.
* p<.10, ** p<.05, *** p<.01.

B. Specialisation, growth trajectories and convergence clubs

A country is more specialised if its scientific output is concentrated in fewer research areas. We hypothesise that there is an inverse relationship between the size of a science system and its degree of specialisation. As a science system grows, its degree of specialisation declines. Our convergence estimates suggest that, at least after 2000, small science systems achieved higher growth rates than large science systems. If our hypothesis is correct, convergence is statistically enforced.

[4] Data taken from the United Nations Common Database (UNCDB) and UNESCO Institute for Statistics Data Centre. Data availability for the intermediate variables, such as the number of researchers per million inhabitants, appears to be biased towards more developed countries.

[5] The same models were tested for total output and output per unit of GDP. The results confirm the outcomes of Table 1. In 1993-2000, there is neither convergence nor divergence in total output and conditional convergence in output per unit of GDP. In 2000-2008, all models show conditional convergence.

Understanding aggregate scientific specialisation requires that we account for three distinct but interdependent variables: the number of research domains in which a country is active as an indication of scientific variety, average output per research domain as an indication of the intensity of scientific activity, and the distribution of output across research areas [27].

We have used the coefficient of variation to measure how output is dispersed among the 169 research areas (Figure 1).[6] There is an inverse relationship between size and specialisation. Figure 2 confirms that large science systems are active in more research areas than small systems, and that large science systems produce more output per research area than small systems. The nature of the relation between output and activity is, however, by no means straightforward. The intensity of activity shows a strong log-linear relationship, whereas the relationship between output and the range of activity has the shape of an S-curve.

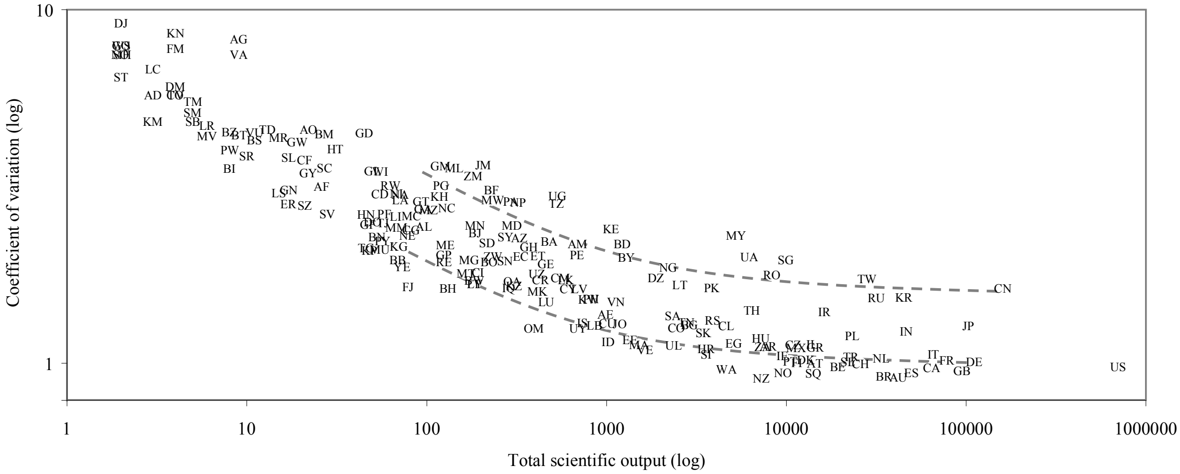

Figure 1. Total scientific output versus the distribution of output across research areas, 2008 (logarithmic scales)

Note: Country codes correspond to ISO 3166-1. Dashed curves drawn by hand.

[6] Concentration and specialisation indices are used in a wide variety of disciplines to measure how data are distributed across populations and samples. There are examples from international trade [28] L. De Benedictis and M. Tamberi, "Overall specialization empirics: Techniques and applications," *Open Economies Review,* vol. 15, pp. 323-346, Oct 2004., technology and R&D [29] F. Malerba and F. Montobbio, "Exploring factors affecting international technological specialization: the role of knowledge flows and the structure of innovative activity," *Journal of Evolutionary Economics,* vol. 13, pp. 411-434, Oct 2003, [30] E. Mansfield, "Composition of R and D Expenditures - Relationship to Size of Firm, Concentration, and Innovative Output," *Review of Economics and Statistics,* vol. 63, pp. 610-615, 1981., market analysis [31] R. Ginevicius and S. Cirba, "Additive measurement of market concentration," *Journal of Business Economics and Management,* vol. 10, pp. 191-198, 2009., and regional economics [32] R. Moreno, R. Paci, and S. Usai, "Geographical and sectoral clusters of innovation in Europe," *Annals of Regional Science,* vol. 39, pp. 715-739, Dec 2005., but the list includes biology [33] R. Gorelick and S. M. Bertram, "Quantifying division of labor: Borrowing tools from sociology, sociobiology, information theory, landscape ecology, and biogeography," *Insectes Sociaux,* vol. 54, pp. 105-112, 2007. and genetics [34] O. Martínez and M. H. Reyes-Valdés, "Defining diversity, specialization, and gene specificity in transcriptomes through information theory," *Proceedings of the National Academy of Sciences of the United States of America,* vol. 105, pp. 9709-9714, 15 July 2008 2008.. The advantage of the coefficient of variation is that it is not scale-dependent. Any set of equal values produces a coefficient of zero.

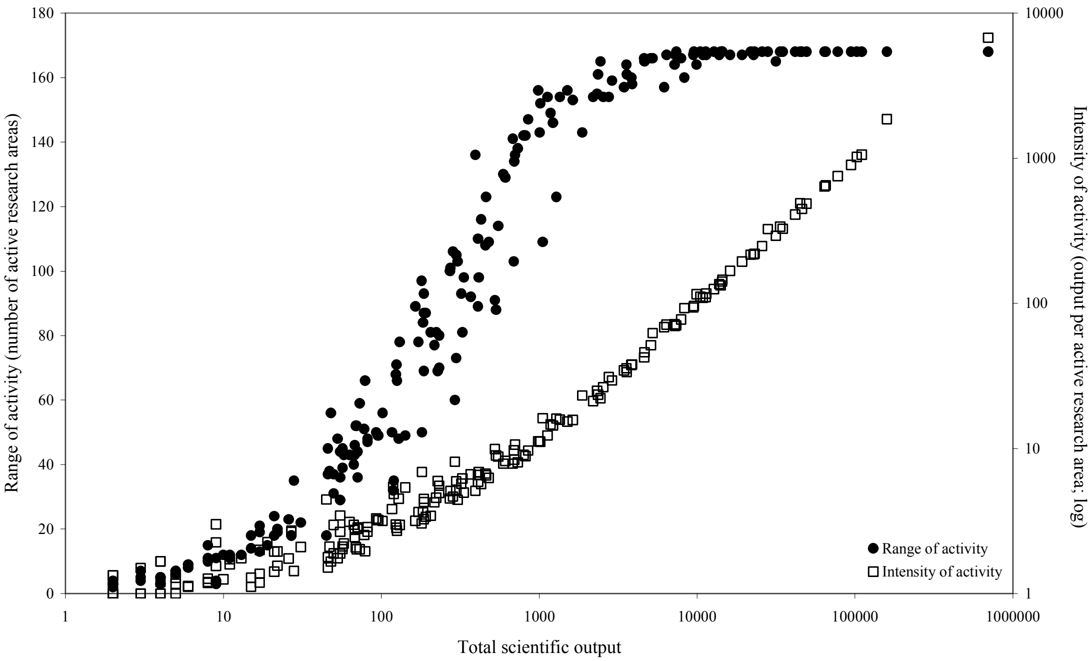

Figure 2. Total scientific output versus range of activity (left axis) and intensity (right axis), 2008

We can infer from Figure 2 that different groups of countries exhibit different patterns of growth and specialisation. Small science systems grow by expanding into new areas; medium-sized science systems grow through a combined increase in intensity and range of activity; and the growth of large science systems, which are active in (nearly) all research areas, almost entirely results from an increase in output intensity.[7] In other words, the relationship between size and specialisation is not uniform but segmented.

One way to find out if different clusters of countries follow different growth trajectories is to examine whether relationships between science system size (in terms of output) and the statistical components of the growth process (intensity; range of activity; coefficient of variation) persist over time. If they do and there is no lateral movement of the curves, countries follow a common trajectory, the S-curve in Figure 2. If they do not and there is lateral movement, there are different country clusters each with their own, particular growth trajectory.

Chow tests, using the years as breakpoints, show that the relationships are identical.[8] The tests show that it is better to treat the data for 1993, 2000, and 2008 as one set than as three separate sets. The absence of lateral movement of the curves and their identical shape suggest that countries move along a common growth trajectory. As a science system grows, it expands its activities into new research areas and intensifies its activities within research areas. Small science systems focus more on expansion, larger systems more on intensification.

Figure 1 shows that there is a considerable number of outliers, representing science systems that have a higher degree of specialisation for their size. These countries – e.g. China, Malaysia, Kenya, Jamaica, South Korea – may have different specialisation strategies than other countries. Common countries follow the growth trajectory of Figure 2 and diversify as they expand into new research areas. The outliers expand and diversify but as they grow their output remains concentrated in fewer areas than in other countries.

V. Structure

Convergence can also be understood as an increasing similarity in output structures, regardless of size. We have compared every country's portfolio with an unweighted average world output structure – using chi-square statistics [35] – to assess to what extent national patterns of specialisation are different from that of the entire

[7] The latter is in part a statistical effect: there is simply no room left in the classification of scientific fields for large science systems to grow by expanding into new research areas. Any diversification in scientific output occurs within rather than between categories and remains out of sight.

[8] When the graphs for the relationship between (the log of) total scientific output and its statistical components are superimposed, the curves appear to be identical. The graphs for 1993 and 2000 are replicas of Figures 1 and 2.

world.[9] When their method is applied to world output structures in 1993, 2000, and 2008, the results show convergence. The majority of countries experienced continuous convergence between 1993 and 2008 (85 countries) or, at the very least, divergence in 1993-2000 followed by convergence in 2000-2008 (61 countries). The trend is towards greater similarity.

Convergence may be a statistical artefact: (1) as countries expand into new research areas, the probability of similarity to world output increases, and (2) while smaller countries can expand into new areas and gradually approach the activity set of larger countries, the largest countries cannot as they are already active in all areas. Substantive agenda setting is, however, a more likely driver of the increasing similarity in national scientific portfolios: similar nations make similar choices.

There are three ways to interpret the dynamics of convergence in scientific portfolios. First, national drivers may be dominant and convergence is an artefact. Alternatively, there may be a worldwide dynamic that underlies the formation of all national agendas and drives their convergence towards a 'unified research agenda'. A third option is the existence of convergence clubs, i.e. clusters of countries whose output structures and science systems are similar while they are distinctly different from those of countries in other clusters. We use factor analysis to find out.

A. *Clustering countries using factor analysis*

It is unrealistic to assume that national scientific portfolios are driven solely by national forces and that similarity between nations is an artefact. Even in the event that funding agencies, universities, and research groups set their agendas entirely autonomously, responding only to global developments within their disciplinary domain, countries still share properties that directly shape the scientific agenda. Think, for example, of similarities in the level of economic development, in links with science-based industry, and in the nature of the social contract between science and society.

This leaves us with the second and third options. If there is a global dynamic that drives scientific agenda setting, we can expect countries to cluster into a decreasing number of ever larger factors and the factors themselves to correlate increasingly strongly. If, on the other hand, there are convergence clubs, the scientific output structures of countries in a club should correlate stronger with those of countries within the club than with the output structures of countries outside the club. We may find that countries cluster into a decreasing number of factors, but there should be little or no correlation between the factors.

We have clustered countries using an orthogonal rotation (Varimax) based on the distribution of their scientific output across 169 research areas. At the default eigenvalue of one (the Kaiser criterion), the result is a factor structure of 37 factors in 1993, 37 in 2000, and 31 in 2008. The Kaiser criterion is known to overestimate the number of factors [36], which is why we have applied parallel analysis to determine the right number of factors [36, 37]. The results of parallel analysis suggest constraining the factor analysis to 11 factors in 1993 and 2000 and to 8 factors in 2008. In 2000, the eleventh factor turns out to consist entirely of loadings below 0.4, which is why we have constrained this particular factor solution to 10 factors. The factors are interpretable and intuitively correct.[10]

The science systems of the world cluster into a declining number of factors, with little correlation among the factors.[11] There does not appear to be a global dynamic in scientific agenda setting. The world divides into discrete scientific convergence clubs. Table 4 shows the portfolios of the eight convergence clubs in 2008. The precise clustering of countries in 1993, 2000, and 2008 can be found in Annex I.

B. *Nature and specialisation pattern of convergence clubs*

The convergence clubs have been named according to the countries in each factor and the salient features of their portfolio. Table 5 presents the scientific specialisations of the countries in each factor in 2008. In the earlier years, many emerging countries clustered together with the former Soviet Union to form a cluster of former Soviet Republics and planned economies. Also, the LDCs were divided among a number of different, smaller

[9] If we were to use the actual (i.e. weighted) structure of world output as a reference point, we would really be asking to what extent national output structures resemble those of the USA, China, Japan, the UK and a few other major scientific producers. This is why we use an unweighted average.

[10] We have also tested an oblique rotation (Direct Oblimin), which assumes that the resulting factors may be correlated. Oblique rotation produces a component correlation matrix that shows no significant correlation among factors. This suggests that there is no global macrostructure and that research agendas are primarily driven by nation-specific forces. A comparison of the rotated component matrix of an orthogonal rotation with the structure matrix of an oblique rotation shows that the factor solutions are essentially the same. The factors represent the same types of clusters, appear in roughly the same order, and contain the same countries.

[11] Even without constraining the factor analysis, the factor structures reflect a growing similarity of national science portfolios. Especially between 2000 and 2008, countries increasingly concentrated at the top of the factor structure. In the unconstrained solutions, the top ten clusters account for 73.3% of countries in 1993, 77.3% in 2000, and 86.0% in 2008. In the top 5, the percentage jumped from 60.6% in 2000 to 74.0% in 2008.

clusters. In 1993 we also found a group of (former) French colonies, including Rwanda, Guinea-Bissau, French Guiana, and Haiti. The names do not always exactly match every single country in a club, but they give a general impression of its nature.

TABLE 4.

UNWEIGHTED AVERAGE SHARE OF SCIENTIFIC CATEGORIES IN TOTAL OUTPUT PER FACTOR IN 2008 (%)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
1 Natural sciences	**42.2**	**29.1**	**39.9**	**60.6**	**64.7**	**31.9**	**40.8**	**51.1**
1.1 Mathematics	3.2	0.7	2.1	6.7	0.6	3.3	2.3	0.8
1.2 Computer and information sciences	8.6	0.6	3.9	1.8	0.9	4.2	1.9	1.9
1.3 Physical sciences	9.2	1.2	7.1	25.8	2.4	5.0	1.9	3.8
1.4 Chemical sciences	7.0	1.7	5.3	14.2	1.4	4.2	7.7	12.1
1.5 Earth and related environmental sciences	4.6	6.8	4.5	6.4	18.9	6.3	7.5	12.0
1.6 Biological sciences	9.5	18.0	17.0	5.7	40.4	8.7	19.4	20.6
2 Engineering and Technology	**29.7**	**5.8**	**14.6**	**20.3**	**6.5**	**18.4**	**11.7**	**9.2**
2.1 Civil engineering	1.4	0.3	0.6	0.8	0.4	0.9	0.1	0.7
2.2 Electrical, electronic, and information engineering	13.1	0.7	5.0	5.4	1.1	6.8	2.7	2.7
2.3 Mechanical engineering	2.9	0.5	1.4	2.7	2.4	2.1	0.9	0.4
2.4 Chemical engineering	1.2	0.2	0.7	0.7	0.0	0.9	0.4	0.4
2.5 Materials engineering	4.3	0.5	2.1	6.4	0.1	2.4	0.8	1.0
2.6 Medical engineering	0.9	0.6	0.8	0.5	0.2	0.3	0.7	0.2
2.7 Environmental engineering	2.1	0.8	1.1	1.4	0.8	2.3	0.9	0.9
2.8/9 Environmental and industrial biotechnology	1.0	1.2	1.0	0.9	0.6	0.4	1.5	1.4
2.10 Nanoscience & Nanotechnology	0.7	0.1	0.5	0.8	0.0	0.2	0.2	0.2
2.11 Other engineering and technologies	2.2	0.9	1.5	0.7	0.9	1.9	3.4	1.3
3 Medical and Health Sciences	**24.0**	**57.7**	**41.4**	**15.2**	**21.6**	**44.7**	**23.9**	**33.2**
3.1 Basic medicine	6.3	8.9	11.6	4.4	5.3	7.3	5.1	9.1
3.2 Clinical medicine	13.7	12.5	25.1	9.2	9.2	28.9	11.2	11.2
3.3 Health sciences	4.0	36.2	4.7	1.7	7.1	8.5	7.5	12.9
4 Agricultural Sciences	**3.5**	**6.7**	**3.5**	**0.7**	**5.8**	**1.8**	**22.6**	**4.3**
4.1 Agriculture, forestry, and fisheries	1.8	3.8	1.6	0.4	3.9	1.2	10.8	2.1
4.2 Animal and dairy science	0.9	1.6	0.9	0.2	0.6	0.3	3.6	1.0
4.3 Veterinary Sciences	0.8	1.4	1.1	0.1	1.3	0.3	8.2	1.2
5 Multidisciplinary Sciences	**0.6**	**0.7**	**0.5**	**3.3**	**1.5**	**3.2**	**1.1**	**2.1**
1-5 Total	100	100	100	100	100	100	100	100

Notes: We use the revised classification of science of the OECD's Frascati Manual to classify the subject areas of the Web of Science (OECD, 2002, p. 67, 2007). The scientific research areas in the revised Frascati classification refer directly to subject areas in the Web of Science. A small number of subject areas was not included or was divided among a number of classes (notably, biotechnology); their classification required some additional effort. The classification is available upon request.

TABLE 5

COUNTRIES AND SCIENTIFIC SPECIALISATION PER CONVERGENCE CLUB IN 2008

Factor	Convergence club name	Countries characteristic of the factor	Main scientific specialisations
1	Emerging economies	Emerging economies of Asia, such as Iran, Malaysia, Taiwan, China, Thailand, Singapore, South Korea, and India; countries of North Africa, such as Egypt, Algeria, Tunisia; New Member States in Eastern Europe, such as Latvia, Lithuania, Poland, and including Finland	computer science; physical sciences; electrical engineering and other domains of engineering
2	Less developed countries 1	Less developed countries in Africa (e.g. Tanzania, Burkina Faso, Angola, Mali, Kenya), South and Central America (e.g. Peru, Haiti, Nicaragua, Guatemala), and Asia (e.g. Cambodia, Laos, Afghanistan, Papua New Guinea)	health sciences (about one third of output involves infectious diseases, parasitology, tropical medicine, and public health); biological sciences
3	High-income industrialised nations	High-income industrialised nations in the EU15 (e.g. Netherlands, UK, Italy, Sweden, Denmark, Germany), the USA and Canada, South America (Brazil, Argentina, Uruguay), and Oceania (Australia, New Zealand, Samoa)	clinical medicine and basic medicine; biological sciences
4	Former Soviet Republics	Twelve former Soviet Republics, including Russia, Azerbaijan, Ukraine, Belarus, Kazakhstan, and Georgia, as well as Bulgaria	chemical sciences; physical sciences; mathematics; materials engineering and electrical engineering
5	Ecological strongholds	Small island nations (e.g. New Caledonia, Bermuda, Seychelles, Bahamas, French Polynesia, Marshall Islands, and Micronesia) and countries with an abundance of species, high biodiversity or a highly characteristic ecosystem (Panama, Namibia, Costa Rica, Belize, Ecuador, Bhutan, Greenland)	earth and environmental sciences; biological sciences of which 85% involves biodiversity research, zoology, entomology, and other biology
6	Former British colonies	Eight of the ten countries in factor 6 are (former) British colonies (Jamaica, Antigua & Barbuda, Kuwait, Brunei, Yemen, Trinidad & Tobago, Bahrain, and Barbados)	clinical medicine; electrical engineering
7	Less developed countries 2	A second, smaller group of less developed countries, including Guinea, the Philippines, Nigeria, Vanuatu, Fiji, and Venezuela)	agricultural sciences; biological sciences (one third consists of plant science); food science and technology (in other engineering and technology)
8	Southern Africa	Countries in Southern Africa (Rwanda, Swaziland, Lesotho, Botswana, South Africa)	biological sciences; chemical sciences; earth and environmental sciences; health sciences (almost 11% of output in infectious diseases, parasitology, tropical medicine, and public health)

Since 1993, the clustering of science systems has changed dramatically (Table 6). The emerging economies have grown exponentially, from a mere 11 countries in 1993 to 17 in 2000 and 53 in 2008. Many of these countries were first located among the former Soviet Republics and planned economies. Between 2000 and 2008 this cluster of countries split into the former Soviet Republics and the emerging economies. Among the Less Developed Countries (LDCs) we see a concentration of countries in fewer clusters. The main cluster of LDCs grew from 38 to 51 countries. While the remaining clusters of LDCs shrank from 37 to 9 countries, the group of ecological strongholds grew and a separate cluster of Southern African science systems emerged.

TABLE 6.

FACTOR STRUCTURES IN 1993, 2000 AND 2008 (NUMBER OF COUNTRIES IN EACH FACTOR BETWEEN BRACKETS)

Factor	1993	2000	2008
Emerging economies	7 (11)	4 (19)	1 (53)
LDCs 1	1 (38)	2 (42)	2 (51)
High-income industrialised nations	2 (34)	1 (33)	3 (36)
Former Soviet Republics and planned economies	3 (36)	3 (37)	•
Former Soviet Republics	•	•	4 (15)
Ecological strongholds	8 (11)	8 (12)	5 (19)
(Former) British colonies	5 (18)	6 (16)	6 (10)
LDCs 2, 3, 4 , 5	4,9,10,11 (37)	5,7 (29)	7 (9)
Southern Africa	•	•	8 (7)
(Former) French colonies	6 (6)	•	•
Other countries	•	9,10 (10)	•
Total number of countries	191	198	200

Notes: The numbers refer to the location of each cluster of countries in the factor analysis. For example, in 2008 the emerging economies are the highest cluster in the factor structure, which means that their portfolio contributes most to explaining the portfolio of world scientific output.

We have run factor analysis across the factor solutions for 1993, 2000, and 2008 to find out which convergence clubs cluster together, using the unweighted average output structure of countries within each cluster as input (Table 7). In 1993 and 2000 the result is a three-factor solution in which the third factor consists of small and heterogeneous clusters of countries that also load on the LDCs. In 2008, only two factors remain.

A clear dichotomy emerges. The world is divided between a group of highly developed – 'established' – science systems (the former Soviet Republics, the emerging economies, and the high-income industrialised nations) and the developing world and former colonies. There is no significant correlation across the divide. There are about eight discrete convergence clubs and perhaps only two: the 'haves' and the 'have-nots'.

TABLE 7

RESULTS OF FACTOR ANALYSIS ACROSS FACTORS

1993	Factor 1	Factor 2	Factor 3
LDCs 1	.804		
(Former) French colonies	.683		
LDCs 2	.657		.413
(Former) British colonies	.614		
LDCs 3	.597		
LDCs 4	.506		
Ecological strongholds	.408		
Former Soviet Republics		.850	
High-income industrialised nations		.758	
Emerging economies		.684	
LDCs 5			.892

2000	Factor 1	Factor 2	Factor 3
Former Soviet Republics	.875		
Emerging economies	.848		
High-income industrialised nations	.824		
LDCs 3		.757	
Ecological strongholds		.746	
LDCs 1		.627	.416
LDCs 2		.577	
(Former) British colonies		a)	
Other countries 1			.749
Other countries 2			.720

2008	Factor 1	Factor 2
Emerging economies	.836	
Former Soviet Republics	.740	
High-income industrialised nations	.720	
(Former) British colonies	.541	
LDCs 1		.739
Southern Africa		.678
Ecological strongholds		.677
LDCs 2		.622

Note: Factor analysis across the unweighted average output structure for each group of countries.
[a)] Factor loading lower than 0.4.

The performance of the apparent 'have-nots' (the lower five country clusters) helps explain the convergence of output levels (Table 8). These relatively small science systems experienced high output growth, driven particularly by an expansion into new areas. Larger science systems among the top three clusters achieved lower growth rates. Most remarkable is the rapid rise of the emerging economies that combined portfolio expansion with a strong intensification of scientific activity.[12]

TABLE 8.

SCIENTIFIC OUTPUT GROWTH EXPERIENCE OF CONVERGENCE CLUBS, 1993-2008 (%) AND DEGREE OF SPECIALISATION IN 2008

	annual output growth	annual change in range of activity	annual change in intensity of activity	annual change in degree of specialisation	coefficient of variation in 2008
Emerging economies	9.9	2.9	10.3	-.18	1.747
High-income, industrialised nations	4.1	0.5	4.5	-0.8	1.839
Former Soviet Republics	1.6	1.6	1.8	-0.9	2.617
LDCs 1	6.6	3.8	4.7	-1.3	3.224
LDCs 2	5.7	2.7	2.7	-0.8	3.188
Southern Africa	4.3	2.1	4.7	0.1	3.351
Former British colonies	5.0	3.0	4.7	0.3	2.643
Ecological strongholds	7.7	4.3	2.7	-1.5	3.877

Note: Compound annual growth rates.

Earlier, we noted a number of countries with a substantially higher degree of specialisation for their size. Among countries with an annual output above 1,000 publications, many of the outliers are emerging economies, such as Singapore, Malaysia, China, and Algeria. Can we attribute the rapid rise of the emerging economies to their strong focus in research?

An independent-samples test shows that between 2000 and 2008 the outliers grew significantly faster than other countries of similar size. The per capita scientific output of the 20 outliers increased at an average annual rate of 11.8% compared to 5.9% for the 48 other countries. Four of the outliers – Russia, Ukraine, Belarus, and Japan – have high focus but low growth. Without these four, the difference in growth rates is obviously more pronounced (14.4% versus 5.6% per year). The strong performance of this cluster of science systems may be the result of a particular institutional architecture, a favourable scientific portfolio, deliberate specialisation policies, or other comparative advantages. We can measure the importance of differences in comparative advantages through a combined analysis of growth and structure.

[12] Our estimates of β- and σ-convergence are not affected when we exclude the emerging economies.

VI. GROWTH AND STRUCTURE

The levels and composition of national scientific output converge simultaneously: they are interdependent processes. Do countries converge as a result of autonomous output growth or due to compositional shifts towards more or less dynamic research areas? In this section we use dynamic shift-share analysis to find out.

Dynamic shift-share analysis is a descriptive method that can tell us whether total scientific output growth in a country is the result of autonomous growth within individual research areas, changes in the distribution of output among research areas, or a combination of the two [38]. We have adapted the model used by Dinc [39] and Mitchell and Carlson [40], substituting the world for the nation, the field for the industry, and the nation for the region.

In dynamic shift-share analysis, the absolute increase in output between two points in time is deconstructed into three effects. The natural growth effect measures the growth in total output that would have occurred if output in all fields had grown at the same rate as total world output, assuming constant field shares in total output. The compositional effect measures the growth of total scientific output attributable to a change in field mix. Countries that specialise in fields that are growing relatively rapidly internationally will show a positive compositional effect; countries that specialise in slow-growing fields show a negative effect. The third effect goes by different names: regional share effect, differential effect, or interaction effect. It measures changes in total output due to the interaction between national output growth and worldwide output growth in a field. We adopt Dinc's interpretation of the third effect as an indication of local strengths and comparative advantages [39].

The results in Table 9 reveal the different mix of growth potential, field mix, and comparative advantages of the eight convergence clubs of 2008 in two periods. It is important to remember that, expressed in percentages, the three effects are communicating vessels: a high positive value for one effect must be offset by a lower (negative) value for another effect, such that the sum of the three effects equals one.

The emerging economies are a special case. This is a cluster of countries that experienced very strong output growth based on the same pattern in both periods: a modest growth effect combined with a significant interaction effect. Scientific output growth in the emerging economies is based on persistent comparative advantages and local strengths.

TABLE 9.

THE RELATIVE CONTRIBUTION OF NATURAL GROWTH (NG), FIELD MIX (FM), AND LOCAL CIRCUMSTANCES (LC) TO TOTAL OUTPUT GROWTH PER FACTOR, 1993-2008

	Emerging economies	High-income, industrialised nations	Former Soviet Republics	LDCs 1	LDCs 2	Southern Africa	(Former) British colonies	Ecological strongholds
1993-2000								
growth	0.52	1.18	1.61	-5.01	3.55	2.86	1.72	-6.03
composition	0.02	-0.00	-0.04	1.22	-0.65	-0.19	0.00	1.18
interaction	0.47	-0.18	-0.57	4.79	-1.91	-1.66	-0.72	5.84
Total								
predicted	4,065	13,302	938	-10	56	159	94	-4
actual	4,158	13,333	991	17	102	191	140	21
2000-2008								
growth	0.43	1.44	8.06	0.81	0.94	0.80	1.56	0.95
composition	0.02	-0.01	-1.07	0.13	0.02	-0.05	0.02	0.00
interaction	0.55	-0.43	-5.99	0.07	0.03	0.25	-0.59	0.05
Total								
predicted	11,024	18,954	304	91	291	846	162	41
actual	11,132	18,971	365	141	335	900	253	72

Note: The growth, composition, and interaction effects are represented as a percentage of the estimated sum total of the three effects.

The high-income, industrialised nations had a consistent pattern characterised by high natural growth and a negative interaction effect. The (former) British colonies had a similar disaggregated growth pattern in both periods. An exaggerated version of the same pattern can be found in the former Soviet Republics, where considerable local weaknesses and an unfavourable (perhaps obsolete) output structure may be held responsible for a deteriorating growth performance.[13]

We can discern the same pattern among LDCs 2 and Southern Africa, but here the pattern was reversed. After 2000 these countries had positive interaction effects, indicating comparative advantages and local strengths. The main cluster of LDCs and the ecological strongholds went from very low output growth, based on a portfolio of small but dynamic fields (a positive

[13] The UNESCO Science Report 2010 [41] UNESCO, "UNESCO Science Report 2010. The current status of science around the world," ed. Paris, France: United Nations Educational, Scientific and Cultural Organization, 2010. points out some of the main problems of Russia's S&T system: an ageing research population, low engagement of university staff in R&D, and an obsolete institutional model and funding system.

compositional effect) and strong comparative advantages or local strengths, to stronger, natural growth (witness the dominance of a positive growth effect).

We have classified countries according to their performance with respect to compositional and interaction effects. The number of countries with both a positive interaction effect and a positive compositional effect increased from 22 in 1993-2000 to 53 in 2000-2008. These countries achieved higher than average output growth thanks to a favourable portfolio and local strengths or comparative advantages. The number of countries with the exact opposite experience – negative interaction and compositional effects – fell from 98 to 47. This apparent favourable shift was offset by an increase (from 29 to 66) in the number of countries that experienced lower-than-average output growth due to comparative disadvantages or local weaknesses, despite a favourable portfolio. The fourth group comprises those that had an unfavourable portfolio, but still achieved higher-than-average output growth thanks to local strengths or comparative advantages. Their number declined slightly from 33 to 25.

These shifts suggest that comparative advantages and local circumstances are more important than scientific agenda setting. Growth is a normal phenomenon. The composition of output is only really an issue in the former Soviet Republics (negative) and the main cluster of LDCs (positive) after 2000. In both periods, the interaction effect is where convergence clubs differentiate strongest.

Table 10.

Indicators of S&T capacity of convergence clubs, 1993-2008

	annual growth in researcher population	researchers per million inhabitants 2008	annual growth in GERD ratio to GDP	GERD as a percentage of GDP 2008	population growth	annual growth per capita GDP 1993-2008	per capita GDP in 2008
Emerging economies	3.7	2730	2.4	0.95	1.3	3.1	9099
High-income, industrialised nations	3.1	4444	1.5	1.77	0.9	2.2	19045
Former Soviet Republics	-4.0	1322	-2.1	0.46	-0.2	3.3	7553
LDCs 1	5.8	110	2.6	0.20	2.5	2.4	1014
LDCs 2	10.6	172	a)	0.12	2.3	1.7	1919
Southern Africa	a)	877	1.0	0.67	1.7	2.8	1896
Former British colonies	7.1	378	-6.7	0.07	2.4	2.2	9094
Ecological strongholds	-3.3	218	2.4	0.26	1.5	2.6	16168

a) Insufficient data.

The interaction effect shows the extent and direction of the influence of comparative advantages and local conditions but not their precise nature. In Table 10 we provide a summary view of some of the most important quantitative indicators. This information corroborates the results of dynamic shift-share analysis for the former Soviet Republics: its negative interaction effect matches low levels of GERD in 2008 and declining ratios of researchers to population and GERD to GDP. In 2008, the lower five clusters had lower levels of GDP, GERD, and researchers than the top three clusters. However, between 1993 and 2008 most achieved substantial improvements in all or some of the indicators. The emerging economies were a consistent good performer on the interaction effect and Table 11 shows how they are rapidly converging on the high-income industrialised countries. In 2008 their levels of achievement were still lower (e.g. GERD as a percentage of GDP), but growth has been substantial faster.

I. Conclusions and discussion

There is convergence in worldwide science. The per capita scientific output of smaller countries grows faster than that of larger countries. The national science portfolios of most of the world's countries are becoming increasingly similar. The evidence on the two interpretations of convergence concurs.

Yet, the world remains divided. Small countries are slowly catching up, but large science systems continue to dominate global science.[14] Growth is a general phenomenon in science, but most countries retain their relative position as a large, medium-sized or small science system. Only a small selection of countries has managed to simultaneously achieve rapid expansion into new research areas and an intensification of activities in each area. These countries are swiftly moving up the rankings.

Science is a highly competitive and dynamic sector. Yet, underneath the dynamics of output growth and portfolio change, worldwide science appears to have a stable structure. The scientific output of nations follows a common growth trajectory. However, the science systems of the world are not converging towards a global scientific agenda or a single system. There is no common development trajectory for science portfolios. Rather, there are convergence clubs, each with their own discrete specialisation pattern and structural characteristics. We found a minimum of eight convergence clubs and a dichotomy between developed and developing nations, the 'haves' and 'have-nots', a dichotomy that appears to be widening. Most countries remain within their convergence club or shift to comparable clubs. Since 1993, few countries have managed to move from the 'haves' to the 'have-nots'. Can convergence clubs escape the restrictions of their specialisation pattern?

[14] A small proportion of countries accounts for the vast majority of publications. In 2008, the ten largest scientific producers in the world, including the USA and China, account for about 70% of world output; the 40 largest for about 95%; the remaining 160-plus countries account for at most 5%.

The science portfolios of countries are shaped by national resource endowments and S&T capacity [42]. Countries have generic comparative advantages (such as a high per capita income or good governance) that explain the quantity of scientific output. We have shown how output size is directly related to the degree of specialisation. Specific comparative advantages (such as resource endowments) form the substance of the agenda and explain why some countries focus more on physics and chemistry and others more on clinical medicine and biodiversity research. Dynamic shift-share analysis shows that comparative advantages (or local strengths and weaknesses) are key to understanding patterns of growth and structural change. In this respect, the most remarkable conclusion is that the rapid rise of the emerging economies as science systems is supported by persistent comparative advantages over other countries and a strong focus in scientific research portfolios. It remains to be seen if their advantage consists of a deliberate policy of scientific growth and specialisation or is fundamentally embedded in the design of the science system.

Longitudinal analysis reveals the inertia of national science portfolios. It takes time to develop and operationalise an agenda, to accumulate structural capacity in the form of skilled scientists, social networks, infrastructures for current and future research, and an institutional framework. Such capacity is not simply put in place but evolves gradually, and this is where part of the complexity of the process lies. Even after twenty years, the former Soviet Union forms a discrete convergence club, while most LDCs and high-income countries stay within their specific clusters. Only the most dynamic countries shift between factors, with the rise of the emerging economies as the most prominent example. In other words, science systems have a good degree of path dependency: early choices carry a lot of weight, especially as science systems grow larger.

A key aspect of such early choice concerns the cultural and political dimensions of decision making [43, cf. 44]. Science is embedded in society and the rules of society extend to science. In some science systems – especially in Europe and the USA – scientists enjoy a great deal of local autonomy and agenda setting is a distributed process. Other systems rely more heavily on coordination and agenda setting is a centralised or top-down process. Notions of the role of science in society – for example, science as an instrument of innovation or as an independent knowledge provider – influence the allocation of resources to and within science.

A major question in science policy concerns the power of coordination and the possibility of guiding the (national) scientific community towards a more desirable research agenda. It is undeniable that science has become a global enterprise. In many fields, the dynamics of agenda setting are driven by a worldwide discourse. An increasing proportion of scientific publications is written in inter-institutional collaboration and, as part of that trend, international collaboration is on the rise. The substance of science knows no boundaries and in this respect we can understand globalisation as a process of local self-organisation by individual scientists, research groups and knowledge institutes.

While scientists may view themselves as part of a global community, national boundaries still matter. Science policy is primarily driven by national interests. Individual actors in the science system may work in an international setting, but the lion’s share of funding originates in national government budgets and investment programmes. Coordination, agenda setting, and policy making also predominantly take place within national science systems. The institutional framework of science remains domestic [45].

The ability of countries to improve their local conditions and escape the strictures imposed by their portfolio depends on the interplay of forces along two dimensions. First, there is the tension between short-term dynamics and long-term stability. This sets the creativity of and competition among self-organising scientists against the initial conditions, structural features, and vested interests of science systems. How much leeway do individual researchers have to set new directions and mobilise the required resources? Then, there is the tension between the complexity of science and the predominance of national policies and institutions. What is the power of policy makers and decision makers to guide the system and change the behaviour of entire communities of actors? These questions are highly relevant where it concerns international competition in science, technology and innovation. Understanding the design and functioning of a science system in all its complexity is crucial to survive in a world of different speeds with intense competition and persistent gaps between rich and poor. For scientists and policy makers alike, selecting the right science portfolio and knowing the competition are key issues.

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